The value of knowing drivers' opportunity cost in Ride Sharing systems

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co-authored with

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2020

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Motivation – Bonuses for drivers

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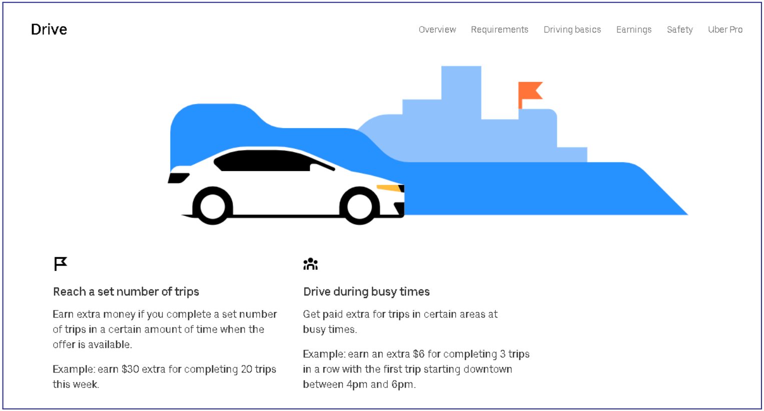

screen shot taken from Uber.com

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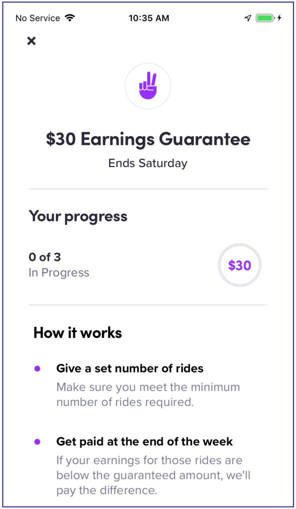

screen shot taken from Lyft.com

Motivation – Bonuses for drivers

Bonus programs are geared towards increasing the number of active drivers on the road.

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Motivation – Bonuses for drivers

Improving Efficiency and Managing Growth in New York's For-Hire Vehicle Sector

New York City Taxi and Limousine Commission and Department of Transportation
Final Report | June 2019

Executive Summary

Traffic congestion in New York City has grown steadily worse since 2010, with average weekday travel speeds in Midtown Manhattan dropping from 6.1 mph in November 2010 to 4.3 mph in November 2018. Though not the only cause, the explosive growth of the for-hire vehicle (FHV) sector, which tripled from fewer than 40,000 vehicles in 2010 to over 120,000 in 2019, is certainly an important factor. As Uber, Lyft, Juno, and Via—app-based, high volume for-hire services—created new, convenient travel options in the outer boroughs, they also added tens of thousands of additional hours of vehicle travel into the Manhattan core (south of 96th Street) each day. The companies saturated the market with vehicles to ensure low wait times and spur demand, causing drivers to spend over 40% of total work time empty and cruising for passengers. Combined with decreasing per-trip pay, this underutilization led to significant declines in driver income.

What is the value of having more drivers on the road?

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What is the value of having more drivers on the road?

...and if indeed there's value:

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What is the value of having more drivers on the road?

...and if indeed there's value:

Can "smart" matching policies increase the equilibrium number of drivers?

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What is the value of having more drivers on the road?

...and if indeed there's value:

Can "smart" matching policies increase the equilibrium number of drivers?

"smart" = informed with drivers' opportunity costs

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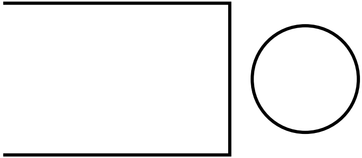

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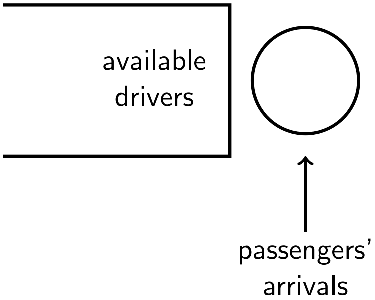

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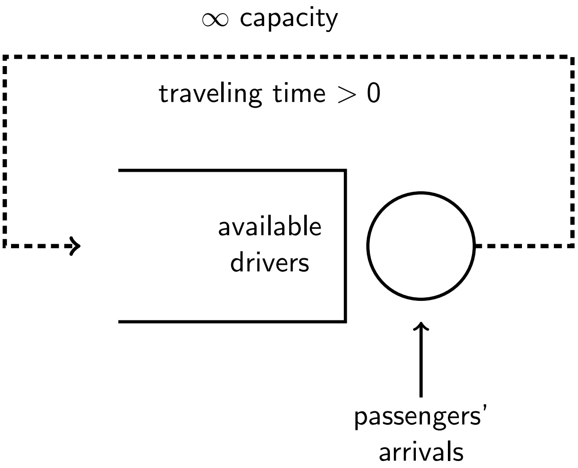

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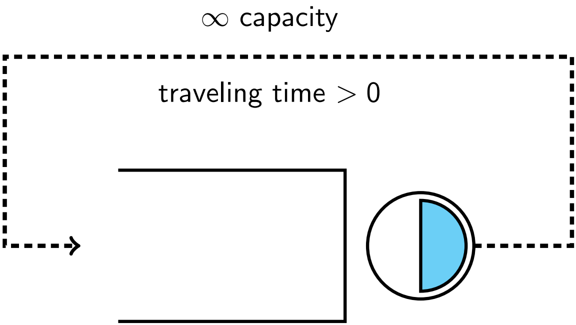
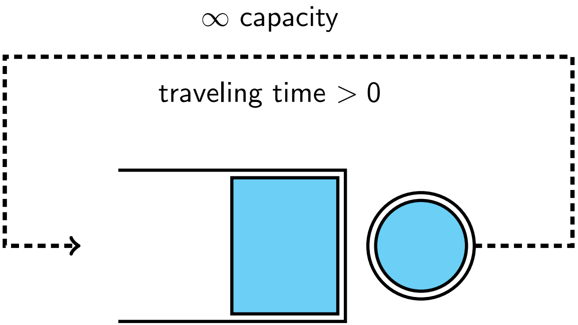


case #1: drivers are 100% busy

Modeling – the naive approach



case #2: 100% demand is filled

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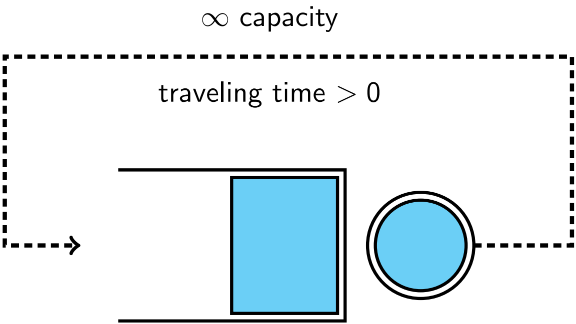

case #2: 100% demand is filled

Many (much more complex) models build on this intuition:

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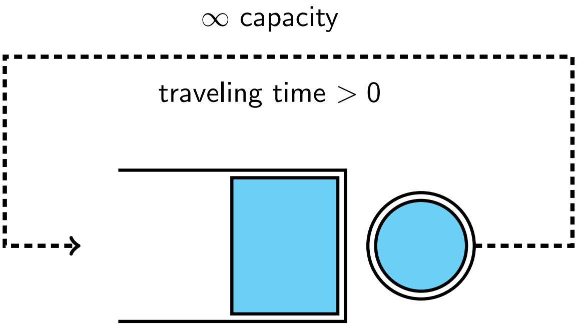

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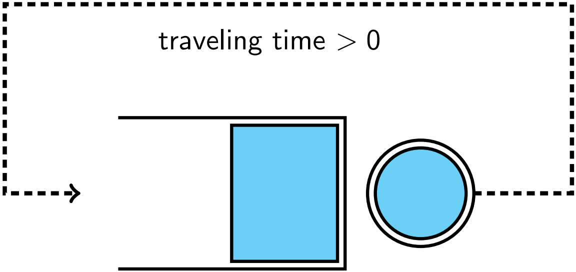
Modeling – the naive approach

∞ capacity



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Queueing models where drivers are short-lived:

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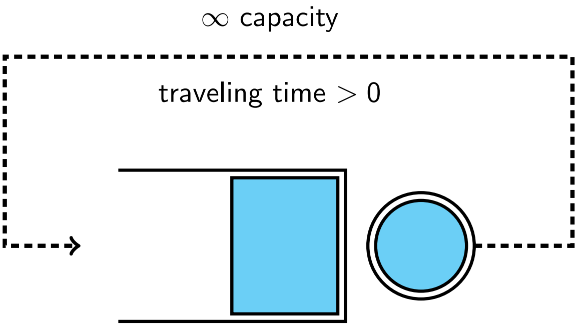

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Modeling – single driver

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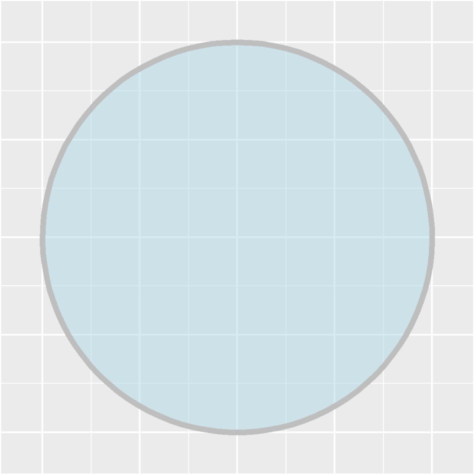
Modeling – single driver

A ring-shaped (continuous) city



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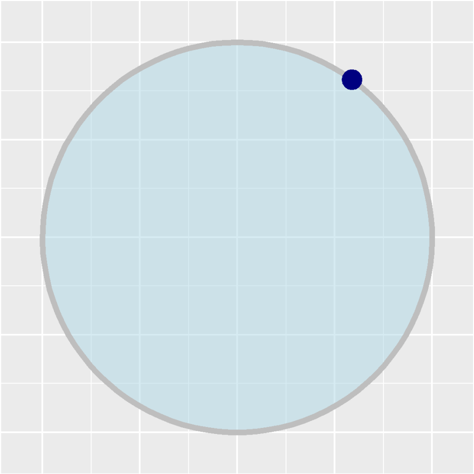
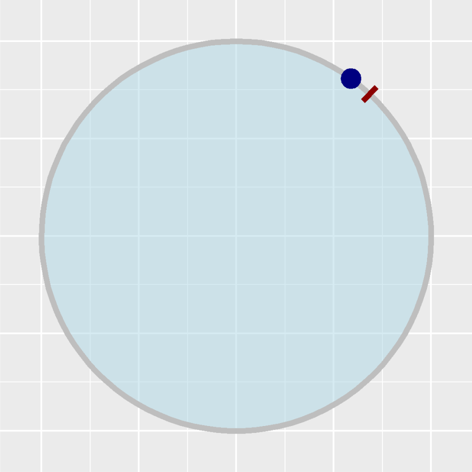
Modeling – single driver

Available drivers circulate the city



Modeling – single driver

Passengers' arrivals are Poisson (λ)
with uniform iid pickup and drop-off locations



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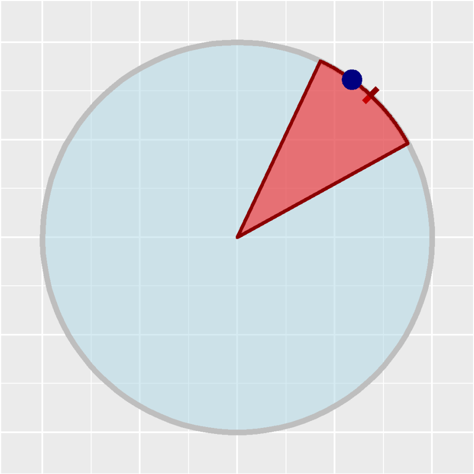
Passengers have a pickup radius ($\delta/2$)



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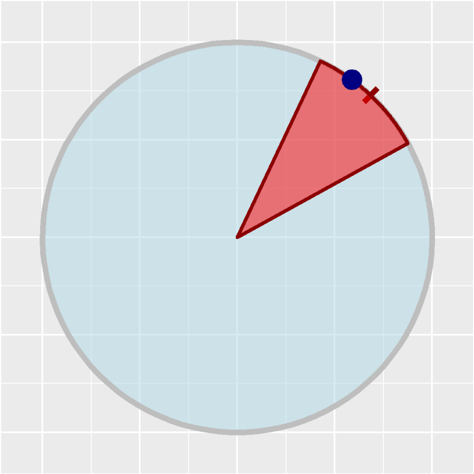
Modeling – single driver

Passengers can only be matched with available drivers within their pickup region



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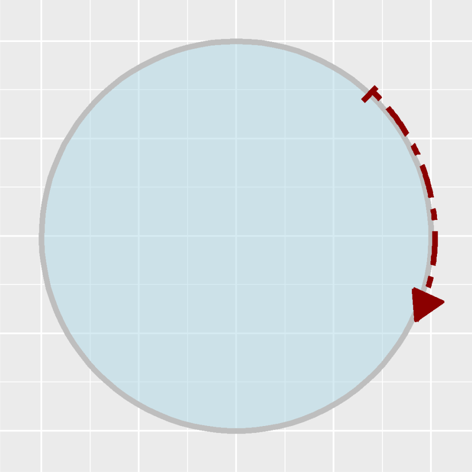
Modeling – single driver

Once matched, the driver becomes *busy* for the duration of the ride, which is random with mean m



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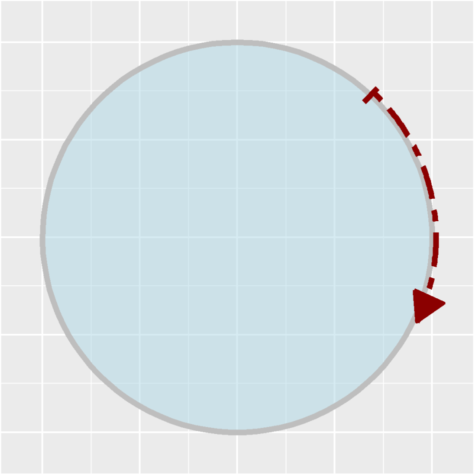
When busy, the driver generates revenue at rate r



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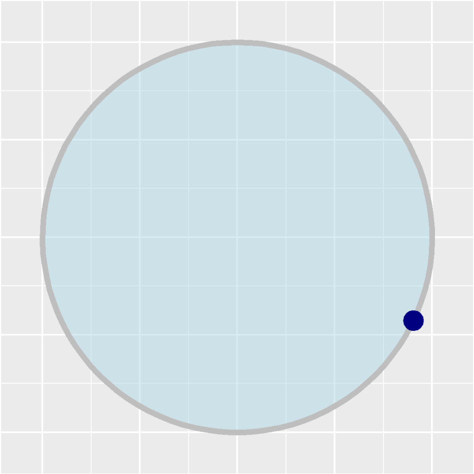
After the ride, the driver becomes available at the drop-off location



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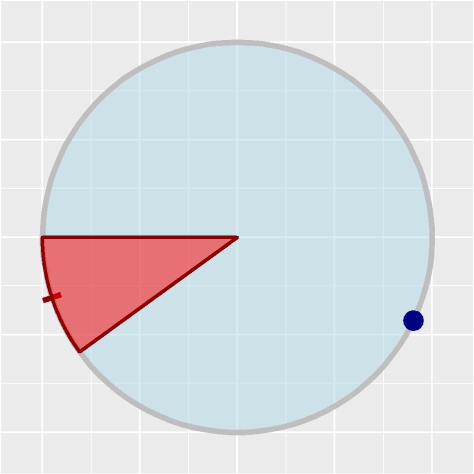
Modeling – single driver

Passengers who can't find available drivers near them are lost



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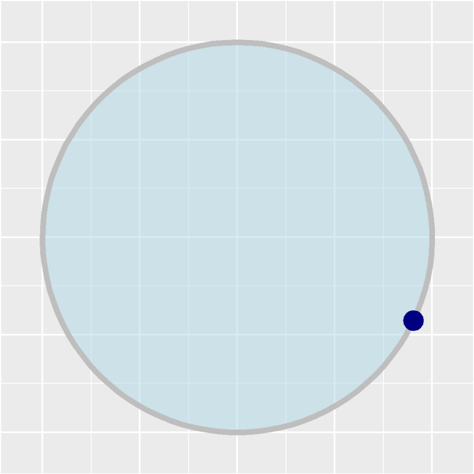

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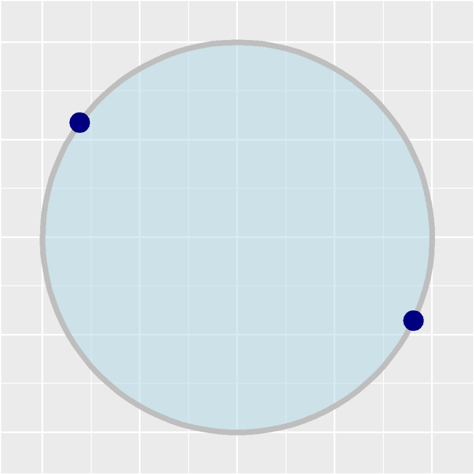
Assume all drivers start with 0 revenue



The value of knowing drivers' opportunity cost in Ride Sharing systems

Ran Snitkovsky

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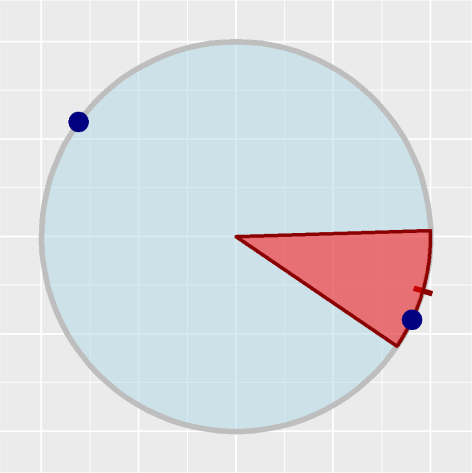

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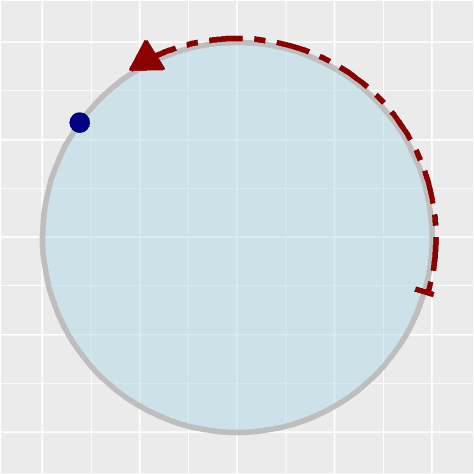
Modeling – two drivers

Drivers accumulate revenue as they complete rides



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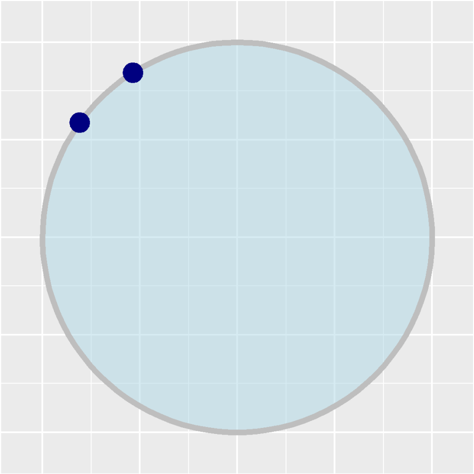
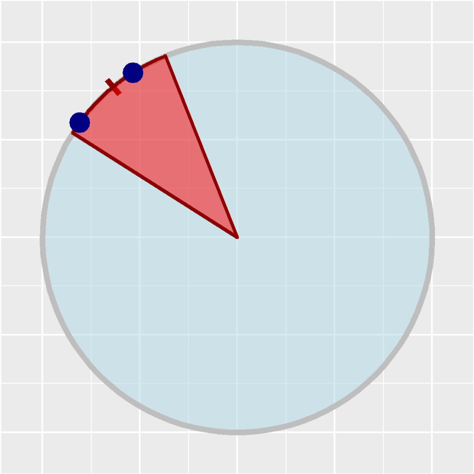


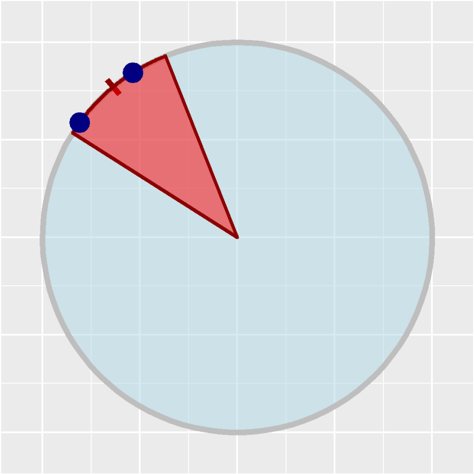
Modeling – two drivers

When 2 (or more) drivers are eligible, we choose the one with minimal revenue



Modeling – two drivers

When 2 (or more) drivers are eligible, we choose the one with minimal revenue (...hence the name MinRev)



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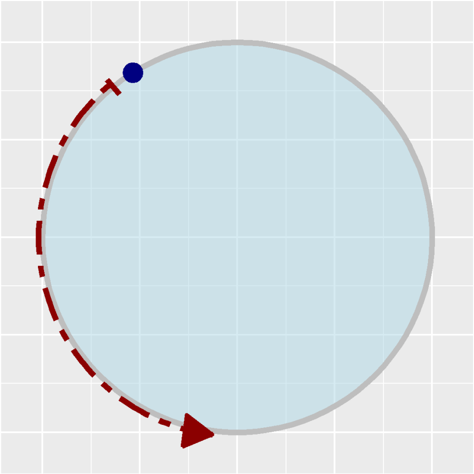

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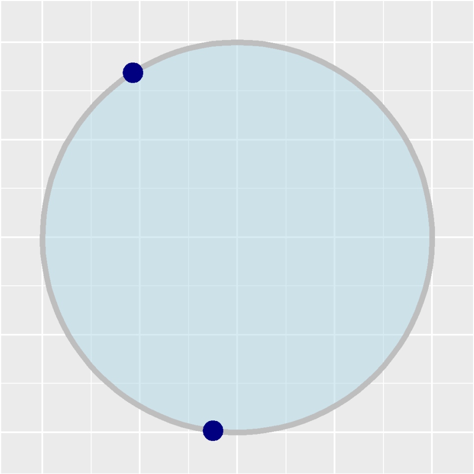

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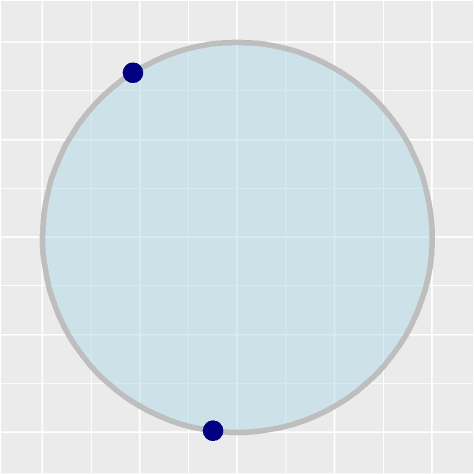
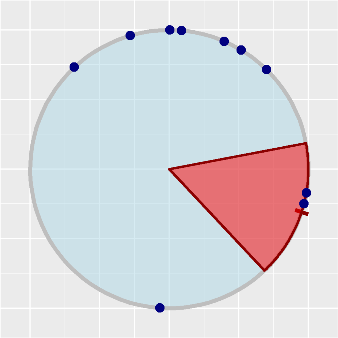
Modeling – two drivers

Dependencies between drivers' states impose difficulties...



Modeling – 10 drivers



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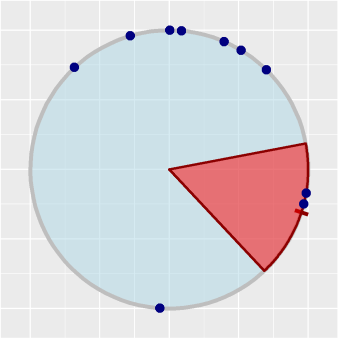

Scaling up the city size:

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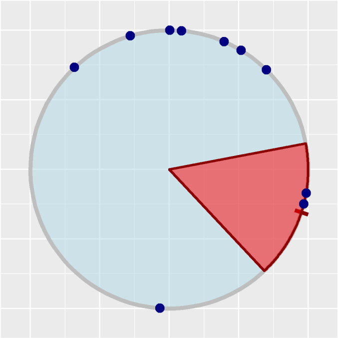
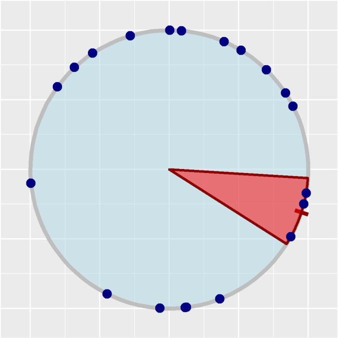


Scaling up the city size:

$$\underbrace{\theta}_{\substack{\text{drivers}\\ \text{intensity}}} \cdot \underbrace{N}_{\substack{\text{scaling}\\ \text{parameter}}} = \underbrace{10}_{\#\text{ drivers}}$$

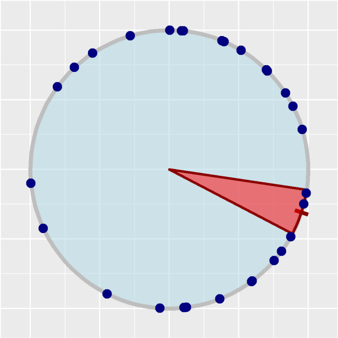
Modeling – 20 drivers



Scaling up the city size:

$$\underbrace{\theta}_{\substack{\text{drivers}\\\text{intensity}}} \cdot \underbrace{N}_{\substack{\text{scaling}\\\text{parameter}}} = \underbrace{20}_{\#\text{ drivers}}$$

Modeling – 30 drivers



Scaling up the city size:

$$\underbrace{\theta}_{\substack{\text{drivers}\\\text{intensity}}} \cdot \underbrace{N}_{\substack{\text{scaling}\\\text{parameter}}} = \underbrace{30}_{\#\text{ drivers}}$$

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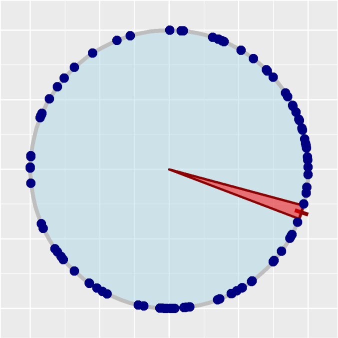
Modeling – ...many drivers



Scaling up the city size:

$$\underbrace{\theta}_{\text{drivers intensity}} \cdot \underbrace{N}_{\text{scaling parameter}} = \underbrace{100}_{\#\text{ drivers}}$$

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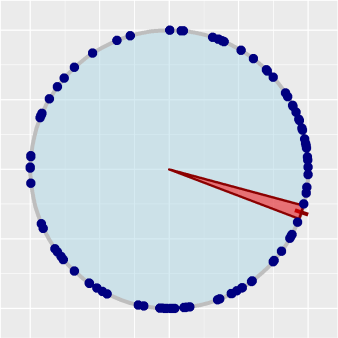
Modeling – ...many drivers



$$\text{passengers arrival rate} = \lambda \cdot N, \qquad \text{pickup radius} = \frac{\delta}{2N}$$

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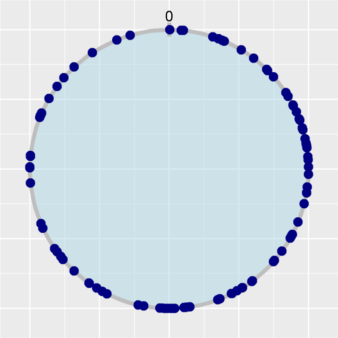
Modeling – ...many drivers



We represent the city by the unit interval $[0, 1)$

The value of knowing drivers' opportunity cost in Ride Sharing systems

Ran Snitkovsky

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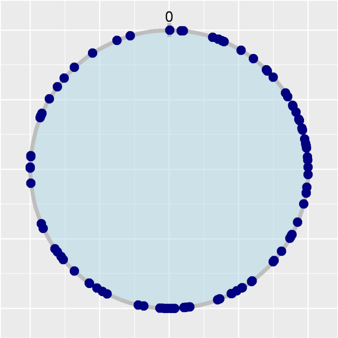

The state at time t is a function:

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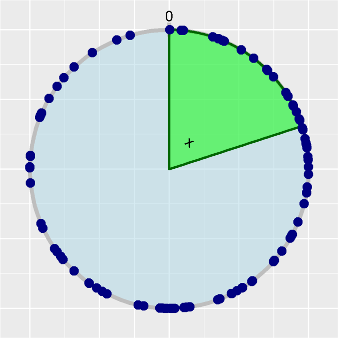

The state at time t is a function:

$$Q(x;t) = \frac{\#\text{ avail. drivers } \in [0,x)}{\underbrace{\#\text{ drivers}}_{=\theta N}}$$

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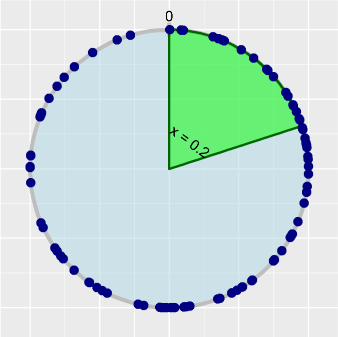
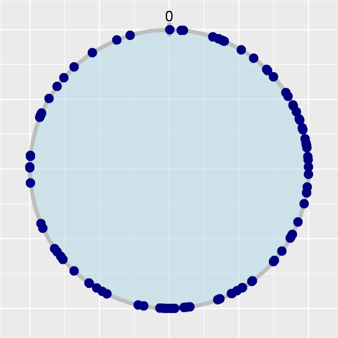
Modeling – ...many drivers



The state at time t is a function:

$$Q(0.2; t) = \frac{\#\text{ avail. drivers } \in [0, 0.2)}{\theta N} = \frac{23}{100}$$

Modeling – ...many drivers



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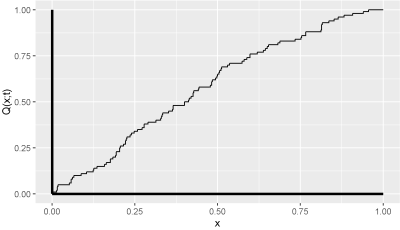
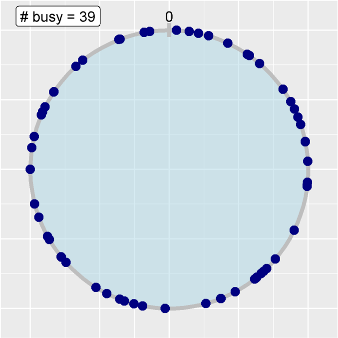


Modeling – ...many drivers



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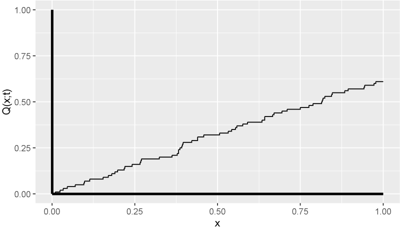
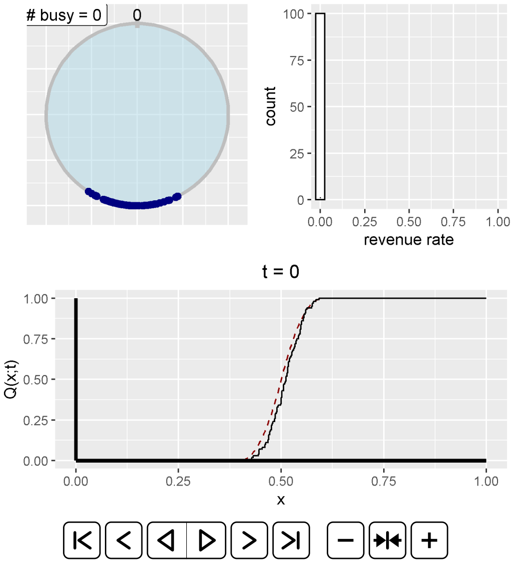


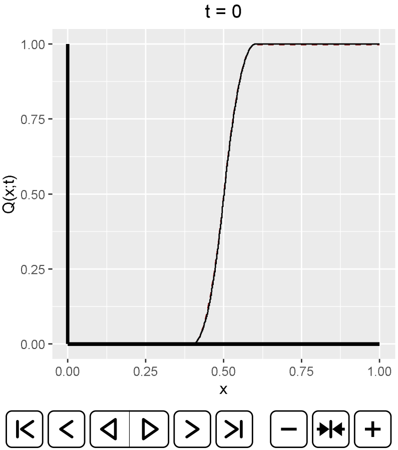
Simulation – many drivers

$N = 100$, $\theta = 1$



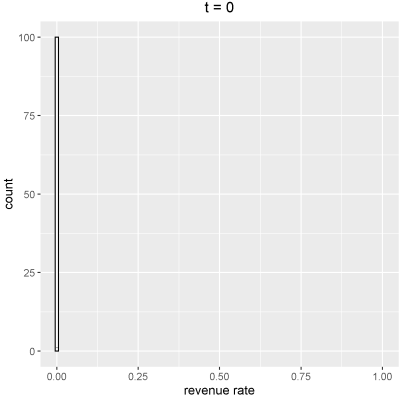
Simulation – large market

$N = 10^4$, $\theta = 1$



Simulation – revenue rate

$N = 100$, $\theta = 1$



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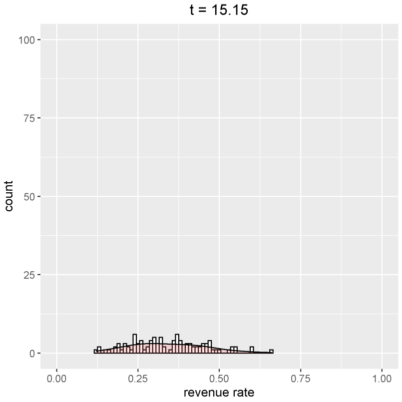

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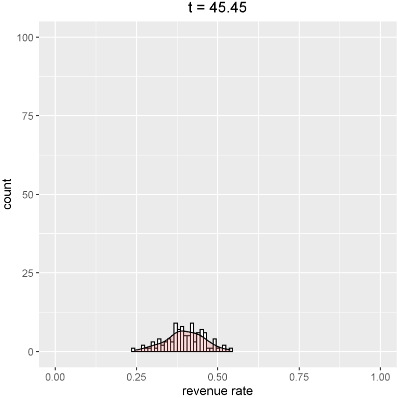
Simulation – revenue rate

$N = 100$, $\theta = 1$



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Simulation – revenue rate

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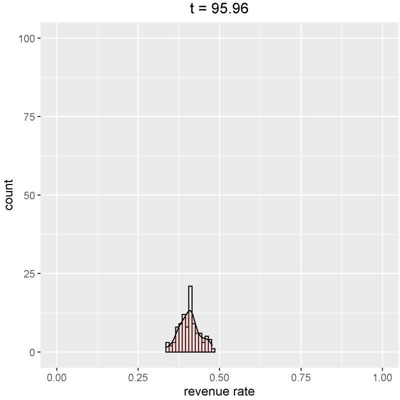

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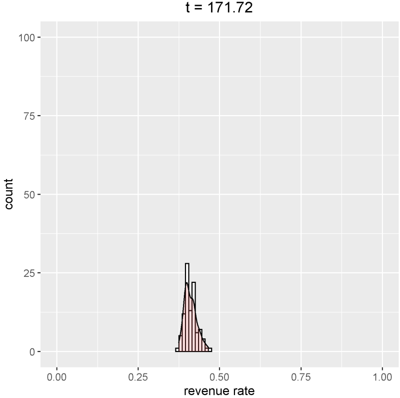

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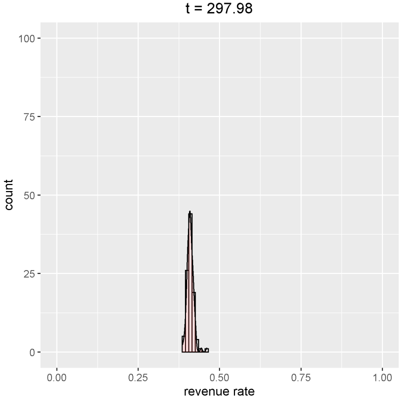

Simulation – revenue rate

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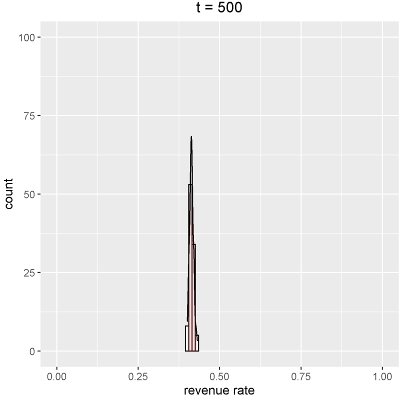

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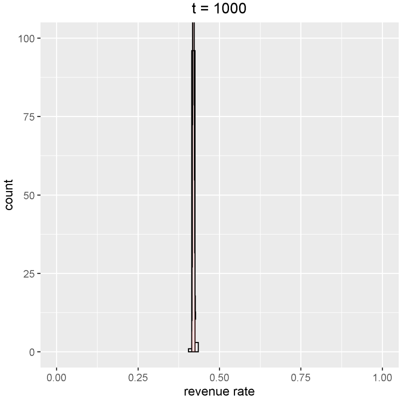

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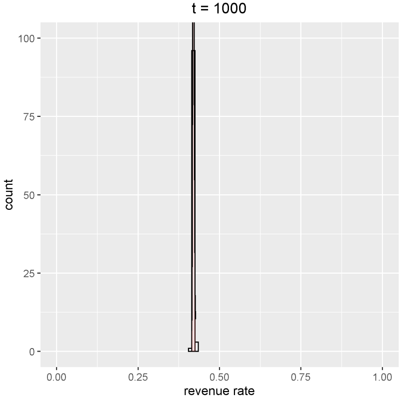

$\Rightarrow$ For the revenue at large t, we don't have to keep track of individual revenues!

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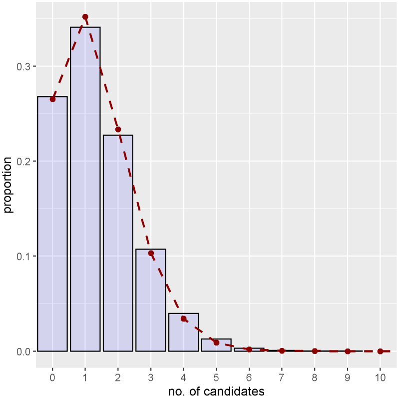
Simulation – spatial distribution

$N = 100$, $\theta = 1$

No. of drivers in a pickup region, $t = 1000$



Mean field – formulation

Mean field – formulation

$Q'(x;t)$ – The derivative of $Q(x;t)$ w.r.t x

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Mean field – formulation

$Q'(x;t)$ – The derivative of $Q(x;t)$ w.r.t x

Loosely speaking, for large N at time t,

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Mean field – formulation

$Q'(x;t)$ – The derivative of $Q(x;t)$ w.r.t x

Loosely speaking, for large N at time t,

$$\#\left\{ \begin{array}{c} \text{avail. drivers} \\ \text{in } x \pm (\delta/2)dx \end{array} \right\} \sim \text{Poisson}\big(Q'(x;t)\theta\delta\big)$$

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$$\frac{\partial}{\partial t}\left(\begin{array}{c}\text{avail. drivers'}\\ \text{in } (0,x]\end{array}\right) = \begin{array}{c}\text{avail. drivers'}\\ \text{inflow}\\ \text{to } [0,x)\end{array} - \begin{array}{c}\text{avail. drivers'}\\ \text{outflow}\\ \text{from } [0,x)\end{array}$$

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$$\frac{\partial}{\partial t}\Big(\theta N \cdot Q(x;t)\Big) = \begin{array}{c} \text{avail. drivers'} \\ \text{inflow} \\ \text{to } [0,x) \end{array} - \begin{array}{c} \text{avail. drivers'} \\ \text{outflow} \\ \text{from } [0,x) \end{array}$$

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$$\theta N \frac{\partial Q(x;t)}{\partial t} = \theta N \cdot \big(1 - Q(1;t)\big)\frac{x}{m} - \begin{array}{c}\text{avail. drivers'}\\ \text{outflow}\\ \text{from } [0,x)\end{array}$$

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corresponding to the limit $N \to \infty$

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Mean field – steady state

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Mean field – steady state

There's a unique *steady-state* Q^* for which

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Mean field – steady state

There's a unique *steady-state* Q^* for which

$$\frac{\partial Q^*(x;t)}{\partial t} = 0, \quad \forall x \in [0,1)$$

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namely, $Q^*(x)$ is constant w.r.t. t

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We show:

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We show: $Q^*(x) = qx$,

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We show: $Q^*(x) = qx$, where $q \in [0,1]$ solves

$$(1-q)\theta = \lambda \cdot \left(1 - e^{-q\theta\delta}\right) \cdot m.$$

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We show: $Q^*(x) = qx$, where $q \in [0,1]$ solves

$$\underbrace{(1-q)\theta}_{\substack{\#\text{ passengers} \\ \text{in system}}} = \underbrace{\lambda \cdot \left(1 - e^{-q\theta\delta}\right)}_{\substack{\text{effective} \\ \text{arrival rate}}} \cdot \underbrace{m}_{\substack{\text{ride} \\ \text{duration}}} .$$

q is thought of as the idling fraction per driver

Mean field – steady state

We define:

$$\lambda^* := \text{steady-state matching rate}$$

Mean field – steady state

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$$\lambda^* := \begin{array}{c}\text{steady-state}\\\text{matching rate}\end{array} = \lambda \int_{s=0}^{1} \left(1 - e^{-Q^{*\prime}(s)\theta\delta}\right) ds$$

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$$= \lambda \left(1 - e^{-q\theta\delta}\right)$$

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Mean field – comparative statics

Mean field – comparative statics

We show:

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Mean field – comparative statics

We show: λ^* is increasing with θ

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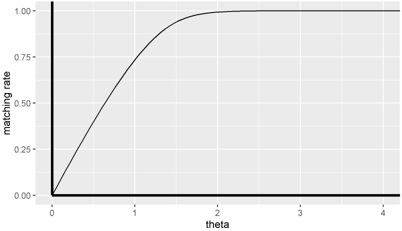

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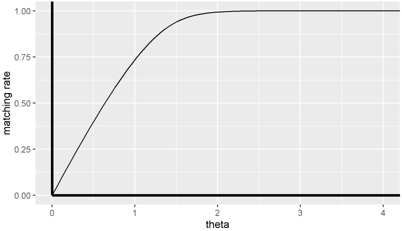
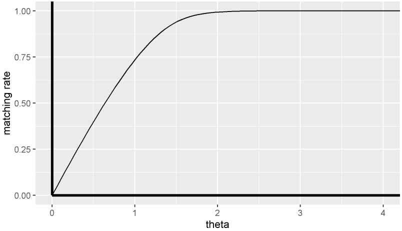


Given λ^* (e.g. $\lambda^* = 0.99 \times \lambda$):

Mean field – comparative statics

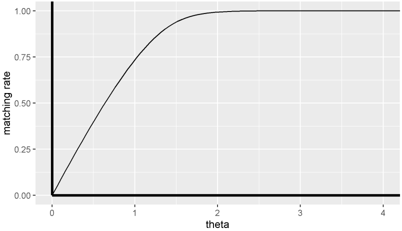
We show: λ^* is increasing with θ



Given λ^* (e.g. $\lambda^* = 0.99 \times \lambda$):
How to choose θ so as to induce a certain pickup standard?

Mean field – comparative statics

We show: λ^* is increasing with θ



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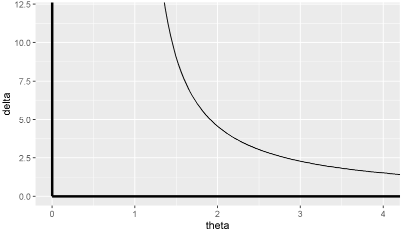

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Key takeaway # 1:

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Key takeaway # 1:

More drivers

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Key takeaway # 1:

More drivers

$\Rightarrow$ Better coverage

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Key takeaway # 1:

More drivers

$\Rightarrow$ Better coverage

$\Rightarrow$ More matches!

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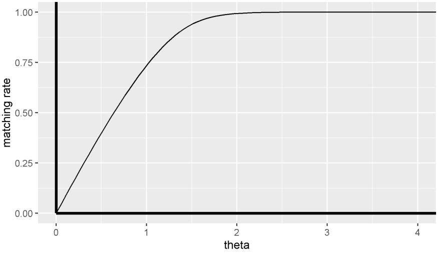
Mean field – comparative statics

We show: λ^* is increasing with θ



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Mean field – comparative statics

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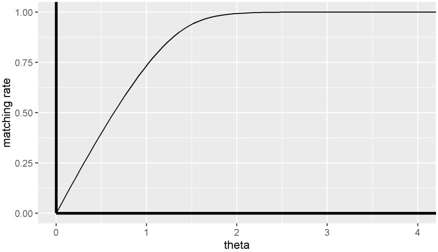

however...

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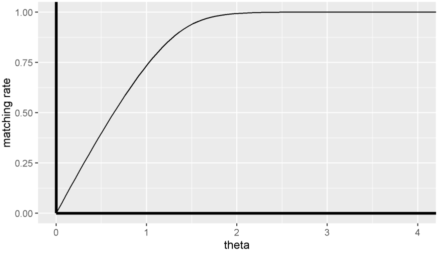
Mean field – comparative statics

We show: λ^* is increasing with θ



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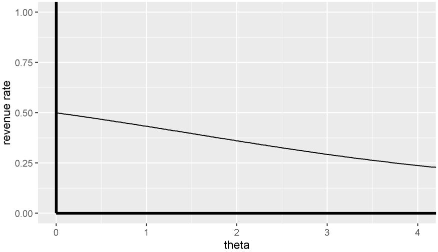

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More drivers $\Rightarrow$ More matches...

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More drivers $\Rightarrow$ More matches...

...but also more idling time $\Rightarrow$ less revenue per driver!

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More drivers $\Rightarrow$ More matches...

...but also more idling time $\Rightarrow$ less revenue per driver!

Assumption:

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More drivers $\Rightarrow$ More matches...

...but also more idling time $\Rightarrow$ less revenue per driver!

Assumption: The quantity θ is formed in equilibrium

More drivers $\Rightarrow$ More matches...

...but also more idling time $\Rightarrow$ less revenue per driver!

Assumption: The quantity θ is formed in equilibrium

How can the platform increase θ?

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Equilibrium – conditions

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Equilibrium – conditions

Drivers make revenue at r when busy

Equilibrium – conditions

Drivers make revenue at $\underbrace{r}_{=1}$ when busy

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Equilibrium – conditions

Drivers make revenue at $\underbrace{r}_{=1}$ when busy

$R^* :=$ steady-state revenue rate

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Equilibrium – conditions

Drivers make revenue at $\underbrace{r}_{=1}$ when busy

$$R^* := \begin{array}{c}\text{steady-state}\\ \text{revenue rate}\end{array} = r \times (\text{busy fraction})$$

Equilibrium – conditions

Drivers make revenue at $\underbrace{r}_{=1}$ when busy

$$R^* := \begin{array}{c}\text{steady-state}\\ \text{revenue rate}\end{array} = r \times (\text{busy fraction}) = r(1 - Q^*(1))$$

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Equilibrium – conditions

Drivers make revenue at $\underbrace{r}_{=1}$ when busy

$$R^* := \begin{array}{c}\text{steady-state}\\ \text{revenue rate}\end{array} = r \times (\text{busy fraction}) = r(1 - Q^*(1))$$

The equilibrium participation rule for a (potential) driver with opportunity cost (OC) κ:

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Equilibrium – conditions

Drivers make revenue at $\underbrace{r}_{=1}$ when busy

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The equilibrium participation rule for a (potential) driver with opportunity cost (OC) κ:

$$\begin{cases} R^* > \kappa \\ \end{cases}$$

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Equilibrium – conditions

Drivers make revenue at $\underbrace{r}_{=1}$ when busy

$$R^* := \begin{array}{c}\text{steady-state}\\ \text{revenue rate}\end{array} = r \times (\text{busy fraction}) = r(1 - Q^*(1))$$

The equilibrium participation rule for a (potential) driver with opportunity cost (OC) κ:

$$\begin{cases} R^* > \kappa & \Rightarrow \quad \text{participate} \\ & \end{cases}$$

Equilibrium – conditions

Drivers make revenue at $\underbrace{r}_{=1}$ when busy

$$R^* := \begin{matrix}\text{steady-state}\\ \text{revenue rate}\end{matrix} = r \times (\text{busy fraction}) = r(1 - Q^*(1))$$

The equilibrium participation rule for a (potential) driver with opportunity cost (OC) κ:

$$\begin{cases} R^* > \kappa & \Rightarrow \quad \text{participate} \\ R^* < \kappa & \end{cases}$$

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Equilibrium – conditions

Drivers make revenue at $\underbrace{r}_{=1}$ when busy

$$R^* := \begin{array}{c}\text{steady-state}\\ \text{revenue rate}\end{array} = r \times (\text{busy fraction}) = r(1 - Q^*(1))$$

The equilibrium participation rule for a (potential) driver with opportunity cost (OC) κ:

$$\begin{cases} R^* > \kappa & \Rightarrow \quad \text{participate} \\ R^* < \kappa & \Rightarrow \quad \text{don't participate} \end{cases}$$

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Equilibrium – heterogeneous drivers

Assume *potential* intensities

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Equilibrium – heterogeneous drivers

Assume *potential* intensities Θ_L of drivers with OC κ_L

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Equilibrium – heterogeneous drivers

Assume *potential* intensities Θ_L of drivers with OC κ_L
Θ_H of drivers with OC κ_H

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Equilibrium – heterogeneous drivers

Assume *potential* intensities Θ_L of drivers with OC κ_L
Θ_H of drivers with OC κ_H

such that

$$\kappa_L < \kappa_H$$

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Equilibrium – heterogeneous drivers

Assume *potential* intensities Θ_L of drivers with OC κ_L
Θ_H of drivers with OC κ_H

such that

$$\kappa_L < \kappa_H$$

and denote

$$\Theta := \Theta_L + \Theta_H$$

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Equilibrium – heterogeneous drivers

Assume *potential* intensities Θ_L of drivers with OC κ_L
Θ_H of drivers with OC κ_H

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$$\kappa_L < \kappa_H$$

and denote

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Our goal:

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Equilibrium – heterogeneous drivers

Assume *potential* intensities Θ_L of drivers with OC κ_L
Θ_H of drivers with OC κ_H

such that

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and denote

$$\Theta := \Theta_L + \Theta_H$$

Our goal: Characterize equilibrium participation rates:

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Equilibrium – heterogeneous drivers

Assume *potential* intensities Θ_L of drivers with OC κ_L
Θ_H of drivers with OC κ_H

such that

$$\kappa_L < \kappa_H$$

and denote

$$\Theta := \Theta_L + \Theta_H$$

Our goal: Characterize equilibrium participation rates:

$$\theta_L \leq \Theta_L,$$

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Equilibrium – heterogeneous drivers

Assume *potential* intensities Θ_L of drivers with OC κ_L
Θ_H of drivers with OC κ_H

such that

$$\kappa_L < \kappa_H$$

and denote

$$\Theta := \Theta_L + \Theta_H$$

Our goal: Characterize equilibrium participation rates:

$$\theta_L \leq \Theta_L, \qquad \theta_H \leq \Theta_H$$

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Equilibrium – heterogeneous drivers

Assume *potential* intensities Θ_L of drivers with OC κ_L
Θ_H of drivers with OC κ_H

such that

$$\kappa_L < \kappa_H$$

and denote

$$\Theta := \Theta_L + \Theta_H$$

Our goal: Characterize equilibrium participation rates:

$$\theta_L \leq \Theta_L, \qquad \theta_H \leq \Theta_H$$

with $\theta := \theta_L + \theta_H$

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Equilibrium – MinRev

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Equilibrium – MinRev

In the previous example,

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Equilibrium – MinRev

In the previous example, with $\Theta_L = 1$ and $\Theta_H = .5$

$$\kappa_L = .35 \quad < \quad \kappa_H = .45$$

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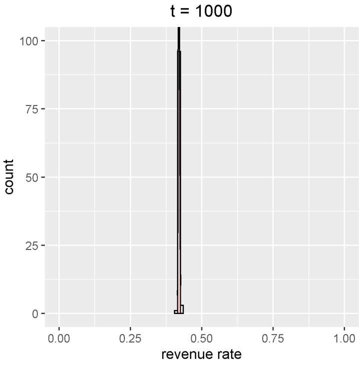

Equilibrium – MinRev

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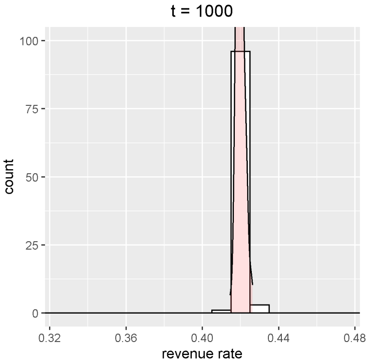

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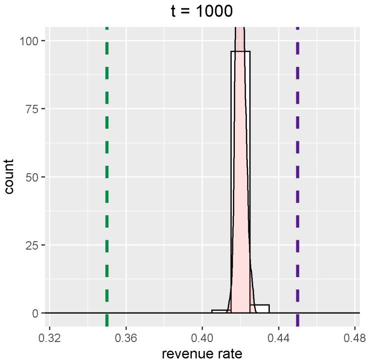

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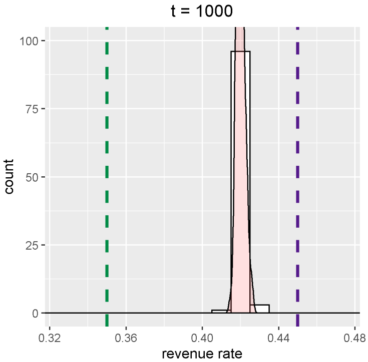

with $\theta = 1$ we have $\kappa_L < R^* < \kappa_H$

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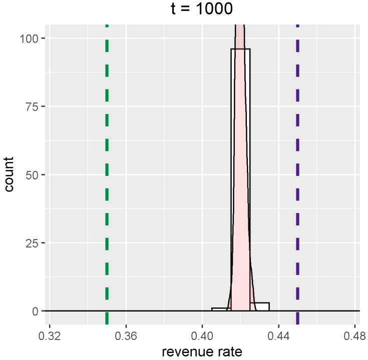

with $\theta = 1$ we have $\underbrace{\kappa_L}_{=.35} < \underbrace{R^*}_{\cong .42} < \underbrace{\kappa_H}_{=.45}$

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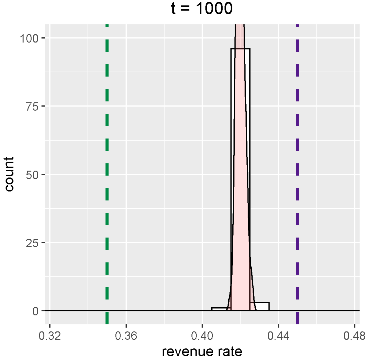
In the previous example, with $\Theta_L = 1$ and $\Theta_H = .5$

$$\kappa_L = .35 \quad < \quad \kappa_H = .45$$



with $\theta = \underbrace{1}_{=\Theta_L}$ we have $\underbrace{\kappa_L}_{=.35} < \underbrace{R^*}_{\cong .42} < \underbrace{\kappa_H}_{=.45}$

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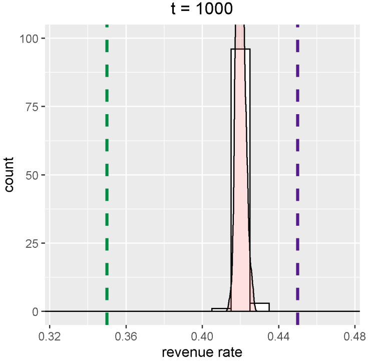
In the previous example, with $\Theta_L = 1$ and $\Theta_H = .5$

$\kappa_L = .35 \quad < \quad \kappa_H = .45$



with $\theta = \underbrace{1}_{=\Theta_L}$ we have $\underbrace{\kappa_L}_{=.35} < \underbrace{R^*}_{\cong .42} < \underbrace{\kappa_H}_{=.45}$

$\Rightarrow$ Only 2/3 of the potential market participate in equilibrium.

In equilibrium, a driver with OC $\kappa \in \{\kappa_L, \kappa_H\}$ participates if

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In equilibrium, a driver with OC $\kappa \in \{\kappa_L, \kappa_H\}$ participates if

$$\frac{\text{absolute revenue rate}}{\kappa} > 1$$

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In equilibrium, a driver with OC $\kappa \in \{\kappa_L, \kappa_H\}$ participates if

$$\frac{\text{absolute revenue rate}}{\kappa} > 1$$

Can we change the matching policy s.t. more potential drivers will participate in equilibrium?

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The MinWeightRev policy

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The MinWeightRev policy

Idea:

The MinWeightRev policy

Idea: Compare *weighted* revenues

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The MinWeightRev policy

Idea: Compare *weighted* revenues instead of *absolute* revenues

The MinWeightRev policy

Idea:	Compare	*weighted*	revenues
	instead of	*absolute*	revenues

$\Rightarrow$ κ_H-drivers have advantage over κ_L-drivers

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The MinWeightRev policy

Idea:	Compare	*weighted*	revenues
	instead of	*absolute*	revenues

$\Rightarrow$ κ_H-drivers have advantage over κ_L-drivers

We need a more elaborate state representation:

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The MinWeightRev policy

Idea:	Compare	*weighted*	revenues
	instead of	*absolute*	revenues

$\Rightarrow$ κ_H-drivers have advantage over κ_L-drivers

We need a more elaborate state representation:

We define $\hat{Q}_L(x;t)$ and $\hat{Q}_H(x;t)$, with

The MinWeightRev policy

Idea:	Compare	*weighted*	revenues
	instead of	*absolute*	revenues

$\Rightarrow$ κ_H-drivers have advantage over κ_L-drivers

We need a more elaborate state representation:

We define $\hat{Q}_L(x;t)$ and $\hat{Q}_H(x;t)$, with

$$\hat{Q}(x;t) = \frac{\theta_L}{\theta_L + \theta_H}\hat{Q}_L(x;t) + \frac{\theta_H}{\theta_L + \theta_H}\hat{Q}_H(x;t)$$

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The MinWeightRev policy

Idea:	Compare	*weighted*	revenues
	instead of	*absolute*	revenues

$\Rightarrow$ κ_H-drivers have advantage over κ_L-drivers

We need a more elaborate state representation:

We define $\hat{Q}_L(x;t)$ and $\hat{Q}_H(x;t)$, with

$$\hat{Q}(x;t) = \frac{\theta_L}{\theta}\ \hat{Q}_L(x;t) + \frac{\theta_H}{\theta}\ \hat{Q}_H(x;t)$$

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MinWeightRev – proof of concept

MinWeightRev – proof of concept

$N = 100$, $\theta = 1.5$

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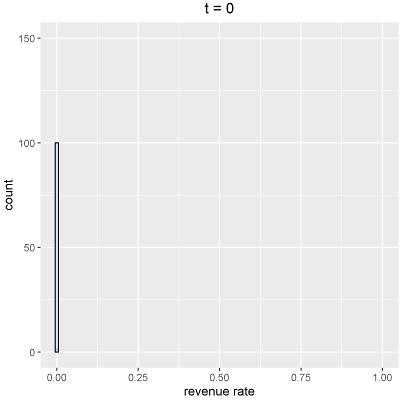
MinWeightRev – proof of concept

$N = 100,\ \theta = 1.5 \quad \theta_L = \Theta_L = 1 \quad \theta_H = \Theta_H = .5$

$\kappa_L = .35 \qquad \kappa_H = .45$



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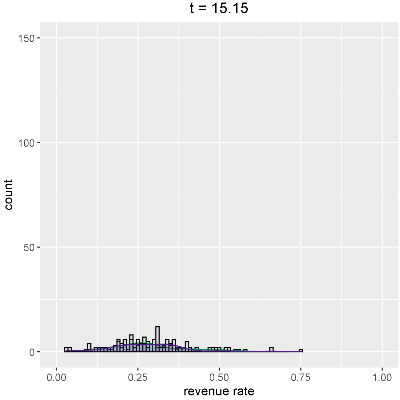
MinWeightRev – proof of concept

$$N = 100,\ \theta = 1.5 \quad \theta_L = \Theta_L = 1 \quad \theta_H = \Theta_H = .5$$
$$\kappa_L = .35 \qquad \kappa_H = .45$$



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MinWeightRev – proof of concept

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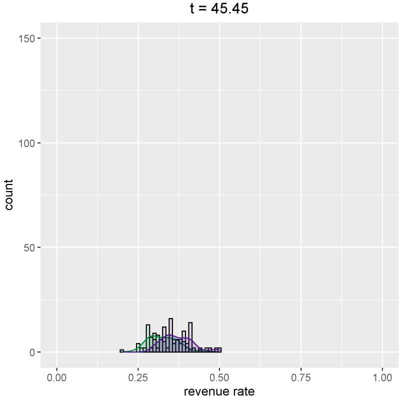

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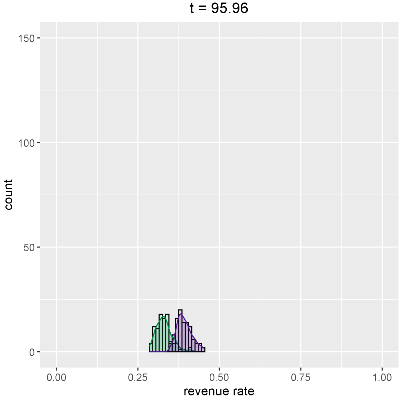

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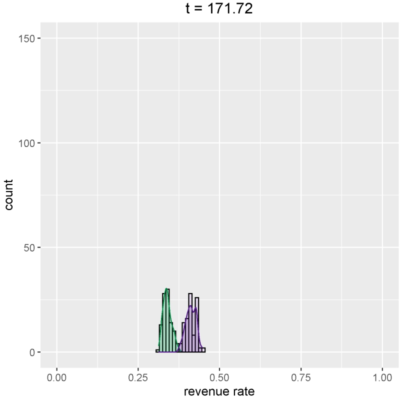

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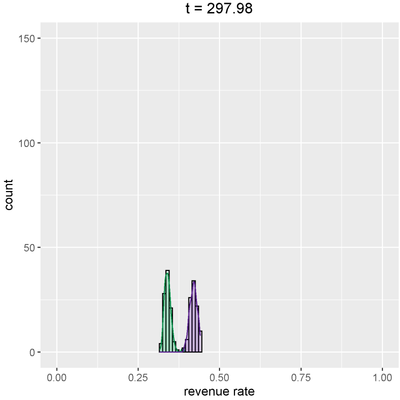

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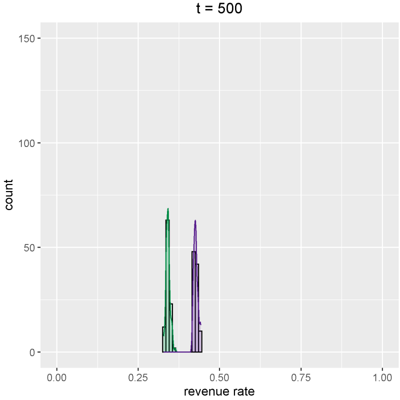

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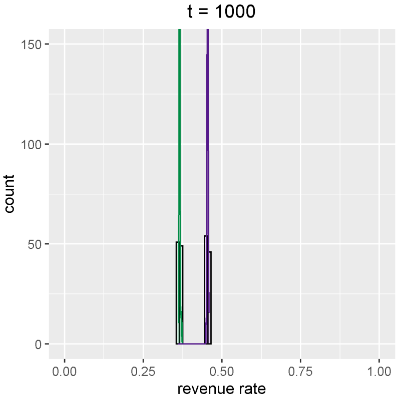

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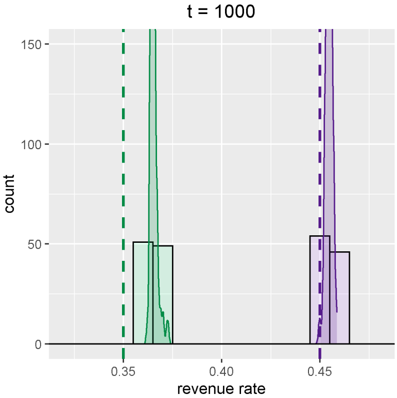

MinWeightRev – proof of concept

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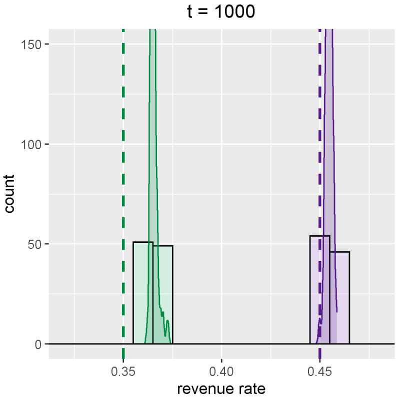

$\Rightarrow$ Equilibrium participation increases by 50% !

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MinWeightRev – challenges

MinWeightRev – challenges

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MinWeightRev – challenges

Problem: Drivers are no longer symmetric

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MinWeightRev – challenges

Problem: Drivers are no longer symmetric

$\Rightarrow$ Dynamics depend on revenue distribution within types

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MinWeightRev – challenges

Problem: Drivers are no longer symmetric

$\Rightarrow$ Dynamics depend on revenue distribution within types

$\Rightarrow$ Mean field system is difficult to formulate

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MinWeightRev – challenges

Problem: Drivers are no longer symmetric

$\Rightarrow$ Dynamics depend on revenue distribution within types

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Solution:

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MinWeightRev – challenges

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Solution: Assume each type $i \in \{L, H\}$ works as a collective

MinWeightRev – challenges

Problem: Drivers are no longer symmetric

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Solution: Assume each type $i \in \{L, H\}$ works as a collective

$\Rightarrow$ We keep track of a single value per type:

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MinWeightRev – challenges

Problem: Drivers are no longer symmetric

$\Rightarrow$ Dynamics depend on revenue distribution within types

$\Rightarrow$ Mean field system is difficult to formulate

Solution: Assume each type $i \in \{L, H\}$ works as a collective

$\Rightarrow$ We keep track of a single value per type:

$$\hat{R}_i(t) := \frac{1}{t} \int_{u=0}^{t} r \cdot \left(1 - \hat{Q}_i(1; u)\right) du, \qquad i \in \{L, H\}$$

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Mean field – MinWeightRev

Given θ_L, θ_H, for each $i, j \in \{L, H\}$, $i \neq j$,

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Mean field – MinWeightRev

Given θ_L, θ_H, for each $i, j \in \{L, H\}$, $i \neq j$,

$$\frac{\partial \hat{Q}_i(x;t)}{\partial t} = \left(1 - \hat{Q}_i(1;t)\right)\frac{x}{m} - \frac{\lambda}{\theta_i}\int\limits_{s=0}^{x}\left(1 - e^{-\hat{Q}_i'(s;t)\theta_i\delta}\right)\hat{D}_i(s;t)ds$$

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where

$$\hat{D}_i(s;t) = \begin{cases} e^{-\hat{Q}_j'(s;t)\theta_j\delta}, & \text{if } \frac{\hat{R}_i(t)}{\kappa_i} > \frac{\hat{R}_j(t)}{\kappa_j} \\ 1, & \text{if } \frac{\hat{R}_i(t)}{\kappa_i} < \frac{\hat{R}_j(t)}{\kappa_j} \end{cases}$$

Mean field – MinWeightRev

Given θ_L, θ_H, for each $i, j \in \{L, H\}$, $i \neq j$,

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If $\frac{\hat{R}_i(t)}{\kappa_i} = \frac{\hat{R}_j(t)}{\kappa_j}$, then

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Mean field – MinWeightRev

Given θ_L, θ_H, for each $i, j \in \{L, H\}$, $i \neq j$,

$$\frac{\partial \hat{Q}_i(x;t)}{\partial t} = \left(1 - \hat{Q}_i(1;t)\right)\frac{x}{m} - \frac{\lambda}{\theta_i}\int_{s=0}^{x}\left(1 - e^{-\hat{Q}_i'(s;t)\theta_i\delta}\right)\hat{D}_i(s;t)ds$$

where

$$\hat{D}_i(s;t) = \begin{cases} e^{-\hat{Q}_j'(s;t)\theta_j\delta}, & \text{if } \frac{\hat{R}_i(t)}{\kappa_i} > \frac{\hat{R}_j(t)}{\kappa_j} \\ 1, & \text{if } \frac{\hat{R}_i(t)}{\kappa_i} < \frac{\hat{R}_j(t)}{\kappa_j} \end{cases}$$

If $\frac{\hat{R}_i(t)}{\kappa_i} = \frac{\hat{R}_j(t)}{\kappa_j}$, then

$$\hat{D}_i(s;t) = [e^{-\hat{Q}_j'(s;t)\theta_j\delta}, 1] \qquad (\hat{D}_i \text{ is set-valued})$$

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Mean field – steady state

Mean field – steady state

There's a unique *steady-state* $\{\hat{Q}_i^*\}_{i\in\{L,H\}}$,

Mean field – steady state

There's a unique *steady-state* $\{\hat{Q}_i^*\}_{i\in\{L,H\}}$, for which

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Mean field – steady state

There's a unique *steady-state* $\{\hat{Q}_i^*\}_{i\in\{L,H\}}$, for which

$$\frac{\partial \hat{Q}_i^*(x;t)}{\partial t} = 0, \quad \forall x \in [0,1),\ i \in \{L,H\}$$

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with

$$\hat{R}_i^* = r \times \begin{pmatrix} \text{busy fraction} \\ \text{for type} \\ i \in \{L,H\} \end{pmatrix}$$

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with

$$\hat{R}_i^* = r \times \left(\begin{array}{c} \text{busy fraction} \\ \text{for type} \\ i \in \{L,H\} \end{array} \right) = r(1 - \hat{Q}_i^*(1))$$

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we show:

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with

$$\hat{R}_i^* = r \times \left(\begin{array}{c} \text{busy fraction} \\ \text{for type} \\ i \in \{L,H\} \end{array} \right) = r(1 - \hat{Q}_i^*(1))$$

we show:

$$\frac{\hat{R}_L^*}{\kappa_L} \geq \frac{\hat{R}_H^*}{\kappa_H}$$

Mean field – steady state

There's a unique *steady-state* $\{\hat{Q}_i^*\}_{i \in \{L,H\}}$, for which

$$\frac{\partial \hat{Q}_i^*(x;t)}{\partial t} = 0, \quad \forall x \in [0,1),\ i \in \{L,H\}$$

with

$$\hat{R}_i^* = r \times \left(\begin{array}{c} \text{busy fraction} \\ \text{for type} \\ i \in \{L,H\} \end{array} \right) = r(1 - \hat{Q}_i^*(1))$$

we show:

$$\frac{\hat{R}_L^*}{\kappa_L} \geq \frac{\hat{R}_H^*}{\kappa_H} \underbrace{\geq 1}_{\text{in equilibrium}}$$

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MinWeightRev vs. MinRev

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MinWeightRev vs. MinRev

If some κ_H-drivers participate

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MinWeightRev vs. MinRev

If some κ_H-drivers participate $\Rightarrow$ all κ_L-drivers should

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MinWeightRev vs. MinRev

If some κ_H-drivers participate $\Rightarrow$ all κ_L-drivers should

$\Rightarrow$ for θ in equilibrium:

MinWeightRev vs. MinRev

If some κ_H-drivers participate $\Rightarrow$ all κ_L-drivers should

$\Rightarrow$ for θ in equilibrium: $\theta_L = \max\{\theta, \Theta_L\}$,

MinWeightRev vs. MinRev

If some κ_H-drivers participate $\Rightarrow$ all κ_L-drivers should

$\Rightarrow$ for θ in equilibrium: $\theta_L = \max\{\theta, \Theta_L\}$, $\theta_H = [\theta - \Theta_L]^+$

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MinWeightRev vs. MinRev

If some κ_H-drivers participate $\Rightarrow$ all κ_L-drivers should

$\Rightarrow$ for θ in equilibrium: $\theta_L = \max\{\theta, \Theta_L\}$, $\theta_H = [\theta - \Theta_L]^+$

In the previous example,

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MinWeightRev vs. MinRev

If some κ_H-drivers participate $\Rightarrow$ all κ_L-drivers should

$\Rightarrow$ for θ in equilibrium: $\theta_L = \max\{\theta, \Theta_L\}$, $\theta_H = [\theta - \Theta_L]^+$

In the previous example, with $\kappa_L = .35$, $\kappa_H = .45$, $\Theta_L = 1$,

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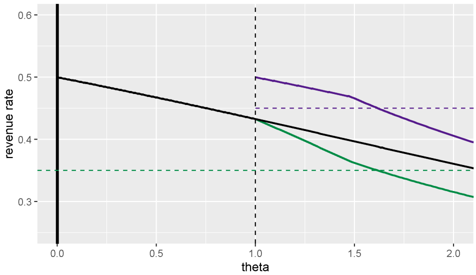
MinWeightRev vs. MinRev

If some κ_H-drivers participate $\Rightarrow$ all κ_L-drivers should

$\Rightarrow$ for θ in equilibrium: $\theta_L = \max\{\theta, \Theta_L\}$, $\theta_H = [\theta - \Theta_L]^+$

In the previous example, with $\kappa_L = .35$, $\kappa_H = .45$, $\Theta_L = 1$,



Key takeaway # 2:

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Key takeaway # 2:

MinWeightRev diverts money from over-paid to under-paid drivers

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Key takeaway # 2:

MinWeightRev diverts money from over-paid to under-paid drivers

$\Rightarrow$ It attracts the higher end of the market

Key takeaway # 2:

MinWeightRev diverts money from over-paid to under-paid drivers

$\Rightarrow$ It attracts the higher end of the market

$\Rightarrow$ Equilibrium number of participating drivers is increased!

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How much better is MinWeightRev vs. MinRev?

Improvement bounds

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Improvement bounds

Define

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Improvement bounds

Define

$$\Phi := \frac{\text{eq. participation under MinWeightRev}}{\text{eq. participation under MinRev}}$$

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Improvement bounds

Define

$$\Phi := \frac{\text{eq. participation under MinWeightRev}}{\text{eq. participation under MinRev}} \qquad \Psi := \frac{\text{eq. matching rate under MinWeightRev}}{\text{eq. matching rate under MinRev}}$$

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Improvement bounds

Define

$$\Phi := \frac{\text{eq. participation under MinWeightRev}}{\text{eq. participation under MinRev}} \qquad \Psi := \frac{\text{eq. matching rate under MinWeightRev}}{\text{eq. matching rate under MinRev}}$$

We show:

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Improvement bounds

Define

$$\Phi := \frac{\text{eq. participation under MinWeightRev}}{\text{eq. participation under MinRev}} \qquad \Psi := \frac{\text{eq. matching rate under MinWeightRev}}{\text{eq. matching rate under MinRev}}$$

We show:

$$\Phi \in (1, 2],$$

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Improvement bounds

Define

$$\Phi := \frac{\text{eq. participation under MinWeightRev}}{\text{eq. participation under MinRev}} \qquad \Psi := \frac{\text{eq. matching rate under MinWeightRev}}{\text{eq. matching rate under MinRev}}$$

We show:

$$\Phi \in (1, 2], \qquad \text{and} \qquad \Psi \in (1, 2)$$

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Extreme improvement example

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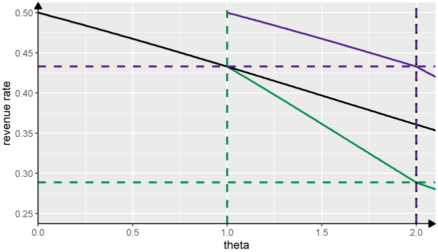
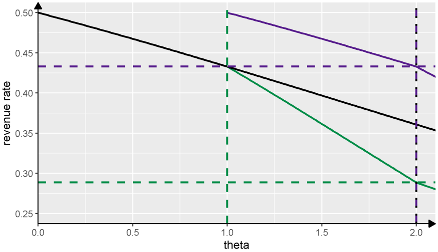
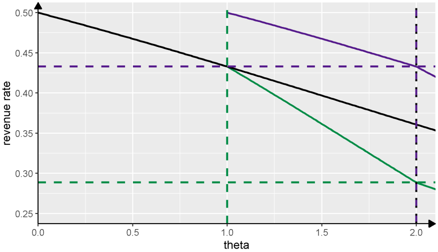


Extreme improvement example

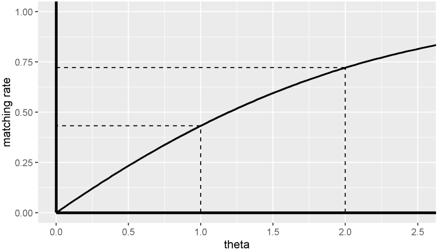


$$\Phi = \frac{2}{1} = 2,$$

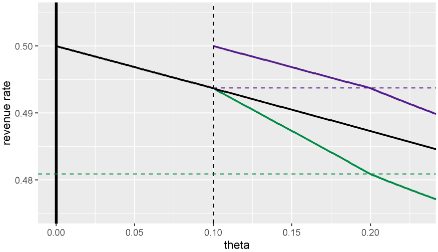
Extreme improvement example



$\Phi = \frac{2}{1} = 2$, and $\Psi = \frac{.71}{.44} \cong 1.61$



Extreme improvement example



$$\Phi = \frac{.2}{.1} = 2,$$

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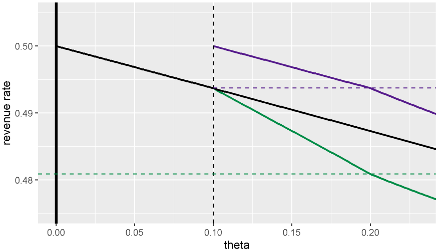
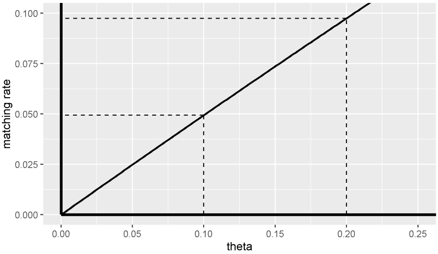
Extreme improvement example



$$\Phi = \frac{.2}{.1} = 2, \text{ and } \Psi = \frac{.097}{.049} \cong 1.98$$



Key takeaway # 3:

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Key takeaway # 3:

Equilibrium participation is up to 2 times more intense in MinWeightRev vs. MinRev

Key takeaway # 3:

Equilibrium participation is up to 2 times more intense in MinWeightRev vs. MinRev

$\Rightarrow$ Matching rate can be improved by up to 100%

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Pickup time improvement

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Pickup time improvement

For a system with $\kappa_L = .2 \quad \kappa_H = .6$

Pickup time improvement

For a system with $\kappa_L = .2 \quad \kappa_H = .6$

$\Theta_L = 2 \quad \Theta_H = 1$

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Pickup time improvement

For a system with $\kappa_L = .2 \quad \kappa_H = .6$

$\Theta_L = 2 \quad \Theta_H = 1$

and a matching-rate goal: $\lambda^* = .99 \cdot \lambda$

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Pickup time improvement

For a system with $\kappa_L = .2 \quad \kappa_H = .6$
$\Theta_L = 2 \quad \Theta_H = 1$

and a matching-rate goal: $\lambda^* = .99 \cdot \lambda$

Goal obtained under:

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For a system with $\kappa_L = .2 \quad \kappa_H = .6$
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Goal obtained under:

MinRev by setting $\delta = 4.56$

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Pickup time improvement

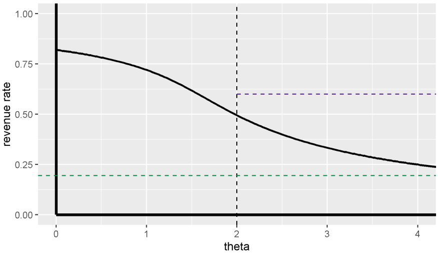
For a system with $\kappa_L = .2 \quad \kappa_H = .6$

$\Theta_L = 2 \quad \Theta_H = 1$

and a matching-rate goal: $\lambda^* = .99 \cdot \lambda$

Goal obtained under:

MinRev by setting $\delta = 4.56$ resulting in $\theta = \Theta_L = 2$



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Pickup time improvement

For a system with $\kappa_L = .2 \quad \kappa_H = .6$
$\Theta_L = 2 \quad \Theta_H = 1$

and a matching-rate goal: $\lambda^* = .99 \cdot \lambda$

Goal obtained under:

MinRev	by setting	$\delta = 4.56$	resulting in	$\theta = \Theta_L = 2$
MinWeightRev	by setting	$\delta = 2.29$		

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Pickup time improvement

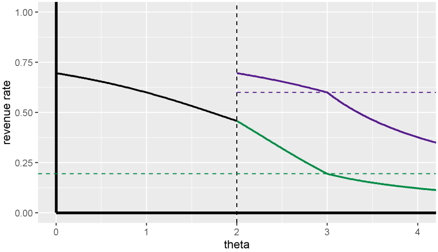
For a system with $\kappa_L = .2 \quad \kappa_H = .6$

$\Theta_L = 2 \quad \Theta_H = 1$

and a matching-rate goal: $\lambda^* = .99 \cdot \lambda$

Goal obtained under:

MinRev	by setting	$\delta = 4.56$	resulting in	$\theta = \Theta_L = 2$
MinWeightRev	by setting	$\delta = 2.29$	resulting in	$\theta = \Theta_L + \Theta_H = 3$



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Pickup time improvement

For a system with $\kappa_L = .2 \quad \kappa_H = .6$
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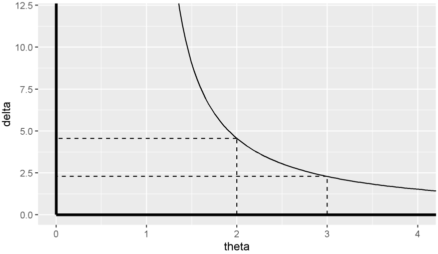
and a matching-rate goal: $\lambda^* = .99 \cdot \lambda$

Goal obtained under:

MinRev	by setting	$\delta = 4.56$	resulting in	$\theta = \Theta_L = 2$
MinWeightRev	by setting	$\delta = 2.29$	resulting in	$\theta = \Theta_L + \Theta_H = 3$



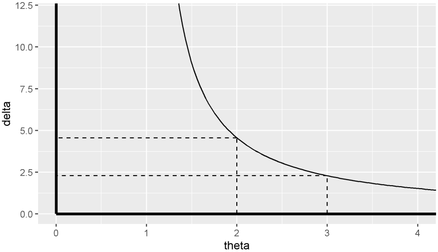
Pickup time improvement

For a system with $\kappa_L = .2 \quad \kappa_H = .6$
$\Theta_L = 2 \quad \Theta_H = 1$

and a matching-rate goal: $\lambda^* = .99 \cdot \lambda$

Goal obtained under:

MinRev	by setting	$\delta = 4.56$	resulting in	$\theta = \Theta_L = 2$
MinWeightRev	by setting	$\delta = 2.29$	resulting in	$\theta = \Theta_L + \Theta_H = 3$



$\Rightarrow$ Pickup standard decreased by 50% !

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Immediate extensions

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Immediate extensions

General spatial pickup/drop-off distributions
$+$ dependencies

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Immediate extensions

General spatial pickup/drop-off distributions
+ dependencies

Two dimensional geometry

Immediate extensions

General spatial pickup/drop-off distributions
+ dependencies

Two dimensional geometry

General OC distribution

Immediate extensions

General spatial pickup/drop-off distributions
+ dependencies

Two dimensional geometry

General OC distribution

Time varying arrival rate (per location)

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Future research directions

Proving convergence in process level
$+$ interchange-of-limits in the general setup

Future research directions

Proving convergence in process level
$+$ interchange-of-limits in the general setup

Designing truth-revealing mechanisms to learn drivers' opportunity costs

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We capture the friction between drivers' spatial coverage and demand loss through novel modeling.

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We capture the friction between drivers' spatial coverage and demand loss through novel modeling.

Smart matching policies attract more drivers to participate,

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Wrap-up

We capture the friction between drivers' spatial coverage and demand loss through novel modeling.

Smart matching policies attract more drivers to participate, improving spatial coverage and system throughput.

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We capture the friction between drivers' spatial coverage and demand loss through novel modeling.

Smart matching policies attract more drivers to participate, improving spatial coverage and system throughput.

The improvement is quantifiable,

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We capture the friction between drivers' spatial coverage and demand loss through novel modeling.

Smart matching policies attract more drivers to participate, improving spatial coverage and system throughput.

The improvement is quantifiable, and we derive tight bounds.

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Thank you for listening!

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Intuition for Poisson spatial process

Assume state $\{Q_i(\cdot;t)\}_{i\in\{L,H\}}$ and available κ_i-drivers' locations are iid with cdf $\frac{Q_i(\cdot;t)}{Q_i(1;t)}$.

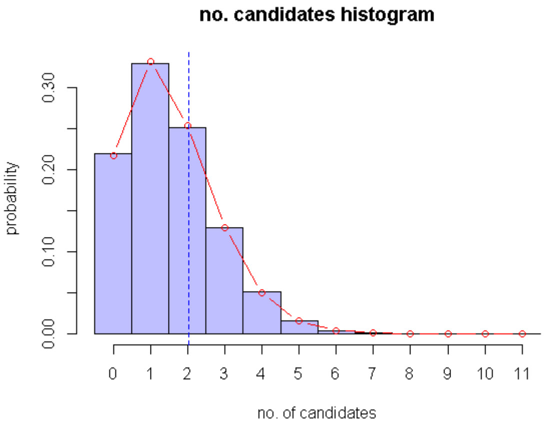
Prob. of κ_i-driver available within the pickup region around $s \in [0,1)$:

$$1 - \left(1 - \frac{Q_i(s+\frac{\delta}{2N};t) - Q_i(s-\frac{\delta}{2N};t)}{Q_i(1;t)}\right)^{\theta_i N Q_i(1;t)}$$

$$\cong 1 - \left(1 - \frac{Q_i(s;t) + Q_i'(s;t)\frac{\delta}{2N} - \left(Q_i(s;t) - Q_i'(s;t)\frac{\delta}{2N}\right)}{Q_i(1;t)}\right)^{\theta_i N Q_i(1;t)}$$

$$= 1 - \left(1 - \frac{Q_i'(s;t)\delta}{NQ_i(1;t)}\right)^{\theta_i N Q_i(1;t)} \xrightarrow[N\to\infty]{} 1 - e^{-Q_i'(s;t)\theta_i\delta}$$

Intuition for Poisson spatial process



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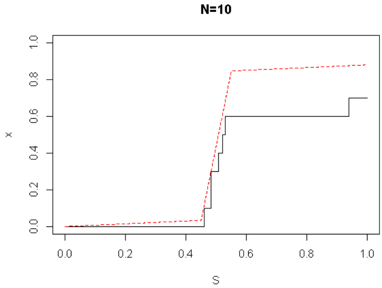
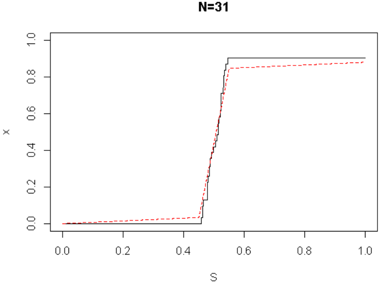
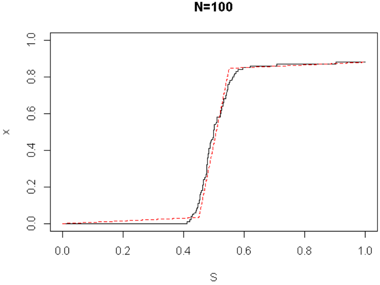
Convergence at process level – MinRev



Convergence at process level – MinRev



Convergence at process level – MinRev



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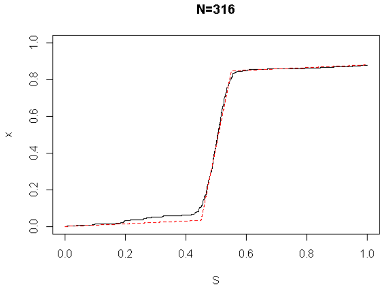
Convergence at process level – MinRev



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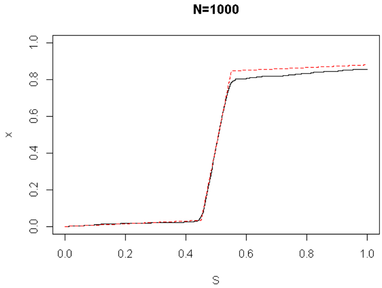

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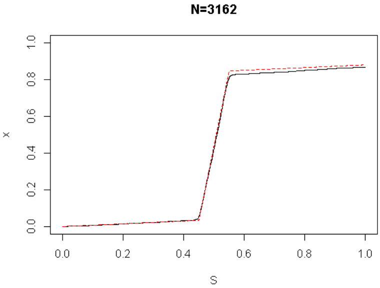

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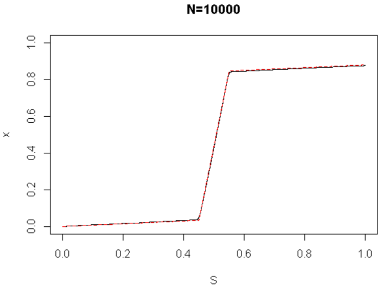

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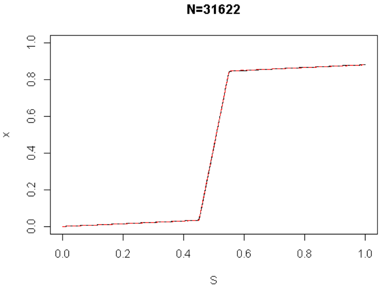
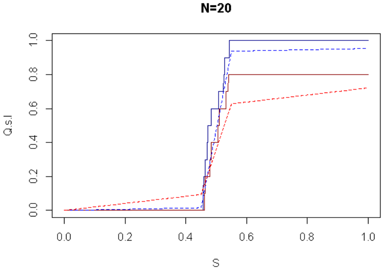
Convergence at process level – MinRev



Convergence at process level – MinWeightRev



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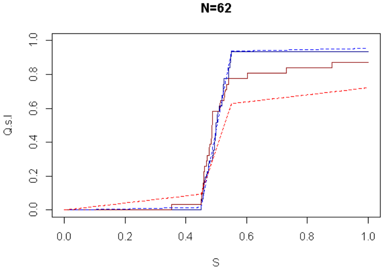
Convergence at process level – MinWeightRev



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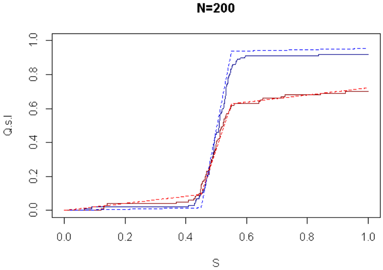
Convergence at process level – MinWeightRev



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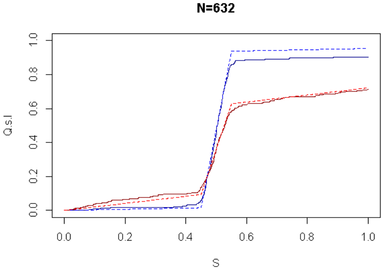
Convergence at process level – MinWeightRev



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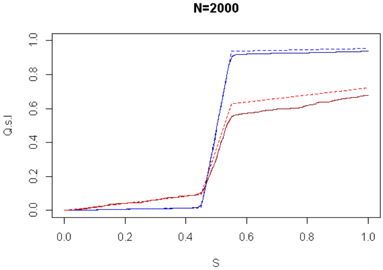
Convergence at process level – MinWeightRev



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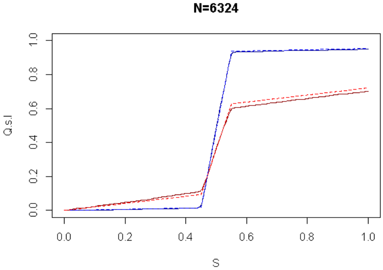
Convergence at process level – MinWeightRev



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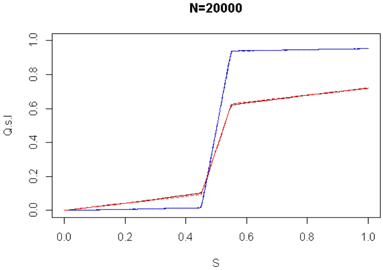
Convergence at process level – MinWeightRev



Convergence of matching rate